Formative Evaluation of College Students' Online English Learning Based on Learning Behavior Analysis

https://doi.org/10.3991/ijet.v17i10.31543

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Abstract—To measure the achievements and progress of college students in online learning, online learning platforms and teachers must pay attention to the formative evaluation of the learning process. The relevant data should be fully utilized to analyze the online English learning behavior of college students, such that online learning platforms and teachers can make formative evaluation of the students' online learning. However, the existing studies on formative evaluation are mostly theoretical. To solve the problem, this paper explores the formative evaluation of college students' online English learning based on learning behavior analysis. Firstly, the density-based spatial clustering of applications with noise (DBSCAN) was adopted to analyze the data samples of college students' online English learning behavior, the evaluation indices were selected for the formative evaluation of the said behavior, and the index weighting method was explained in details. Next, the school precaution function of online English learning was realized through the graph structure data prediction of students' online learning behavior. Based on the proposed graph neural network, the clustering Euclidean distance weight was introduced to measure the similarity between two nodes. In addition, the weight update process was illustrated for the distance weight-based attention mechanism. The proposed formative evaluation approach was proved effective through experiments.

Keywords—learning behavior analysis, online learning, formative evaluation

1 Introduction

Online learning platforms and intelligent terminals provide flexible and pertinent learning modes for college students [1-5]. Online teaching and learning fully reflect the concept of student-oriented teaching, and effectively improve the initiative of students, exerting a huge impact on the teaching and evaluation ideas of traditional offline classroom [6-13]. To improve teaching quality, online learning platforms and teachers have been actively integrating Internet information technology into information teaching mode. Apart from that, they need to pay attention to the formative evaluation of the learning process, which can effectively measure the achievements and progress of college students in online learning, and further optimize the teaching contents and process [14-17]. The formative evaluation should be implemented with broad contents. The relevant data should be fully utilized to analyze the online English learning behavior of college students, such that online learning platforms and teachers can make effective formative evaluation of the students' online learning.

Autonomous learning and self-evaluation are two major topics in the environment of early career teachers (ECTs). Under this framework, new technologies are widely used to develop online tools, which enable students to practice and evaluate their learning progress. Fuentes et al. [18] guided the application and self-evaluation test of practical basic statistics on the computer, and reported the experience of implementing the learning materials and evaluation in the previous school year. Formative evaluation has a great impact on learning, especially online learning. Many scholars have explored the formative evaluation of online learning. But most of them focus on theories or system development, failing to perform much empirical research. Pu and Wang [19] explored the effects of formative evaluation on the attentiveness, course participation, and autonomy of learners, and demonstrated the impacts of formative evaluation on online learning.

According to the *Requirements on College English Course*, it is imperative to apply formative evaluation to students' learning assessment. Niu and Han [20] expounded on the theories and practices of formative evaluation, pointing out that formative evaluation is a superior evaluation tool for language learning, which significantly boosts the language skills of students, and even their overall development. On this basis, they established an effective index system for formative evaluation of online college English learning, and tested the system with fuzzy mathematics. With the rapid development of online learning systems, learning portfolio has been widely adopted to evaluate online learning performance. Chen et al. [21] combined four computational intelligence theories into an evaluation plan for learning performance, and determined the evaluation rules of learning performance, using the network-based learning portfolio. Experimental results show that the plan achieved comparable evaluation results as grade summary evaluation.

So far, many relevant studies have been conducted based on the data of college students' online learning behavior. Most of them extract behavioral features through feature engineering, and build data models by traditional machine learning approaches. However, the analysis effect is far from satisfactory, due to the neglection of the hidden relationship between learning behavioral features. Besides, the existing studies on formative evaluation are mostly theoretical. Few scholars have formatively evaluated the learning of college students on online learning platforms.

Taking online English learning as an example, this paper ores the formative evaluation of college students' online English learning based on learning behavior analysis. Section 2 adopts the density-based spatial clustering of applications with noise (DBSCAN) to analyze the data samples of college students' online English learning behavior, selects the evaluation indices for the formative evaluation of the said behavior, and explains the index weighting method in details. Section 3 realizes the school precaution function of online English learning through the graph structure data prediction of students' online learning behavior, introduces the clustering Euclidean distance weight to measure the similarity between two nodes, based on the proposed graph neural network, and illustrates the weight update process for the distance weight-based attention mechanism. The proposed formative evaluation approach was proved effective through experiments.

2 Behavior analysis

This paper performs cluster analysis on college students' online English learning behavior from four aspects: learning attitude, communication and collaboration, resource utilization, and self-reflection.

The DBSCAN can measure the distribution density of data samples on college students' online English learning behavior, without being limited by the number of classes, and effectively recognize noisy samples and abnormal samples. The key of the algorithm is to determine the suitable neighborhood parameters. Let $E=\{a_1,a_2,..,a_n\}$ be the data sample set of college students' online English learning behavior. Then, the relationship between a data sample and its neighborhood can be defined as follows:

For a data sample a_i in the sample space E, the data samples a_j, whose distance from the data sample is no greater than ϕ, form a set called the ϕ-neighborhood of a_i:

$$M_{\varphi}\left(a_i\right)=\left\{a_j \in E \mid DIS\left(a_i,a_j\right)\leq\varphi\right\} \tag{1}$$

$$\left|M_{\varphi}\left(a_i\right)\right|=\left\{a_j \in E \mid DIS\left(a_i,a_j\right)\leq\varphi\right\} \tag{2}$$

If a_i is a core sample in E, and if it belongs to the ϕ-neighborhood of a_i, then a_j is directly density-reachable from a_i. If there exist other data samples between a_i and a_j making the sample series satisfy the condition for sequential directly density-reachability, i.e., there exist $t_1,t_2,...,t_m$, where $t_1=a_i$, $t_m=a_j$, and t_{i+1} is directly density-reachable from t_i, then a_j is density-reachable from a_i. If there exists a data sample a_l making both a_i and a_j density-reachable via a_l, then a_i and a_j are density-connected.

This paper employs the weighted Euclidean distance method to determine the neighborhood radius of data samples in E. The function $DIS(a_i,a_j)$ measuring the distance between data samples needs to satisfy four properties: (1)Nonnegativity: $DIS(a_i,a_j)$ is always greater than zero; (2) Identity: If and only if $a_i=a_j$, $DIS(a_i,a_j)$ equals zero; (3) Symmetry: $DIS(a_i,a_j)$ equals $DIS(a_i,a_j)$; (4) Triangular inequality: $DIS(a_i,a_j)$ is smaller than the sum of $DIS(a_i,a_l)$ and $DIS(a_l,a_j)$.

For given data samples $a_i=(a_{i1},a_{i2},...,a_{im})$ and $a_j=(a_{j1},a_{j2},...,a_{jm})$, their distance can be characterized by the Minkowski distance:

$$DIS_{nl}\left(a_i,a_j\right)=\left(\sum_{v=1}^{m}\left|a_{iv},a_{jv}\right|^{t}\right)^{\frac{1}{t}} \tag{3}$$

When t=2, formula (3) changes into Euclidean distance:

$$DIS_{CQ}\left(a_i,a_j\right)=\left\|a_i-a_j\right\|_2=\sqrt{\sum_{v=1}^{m}\left|a_{iv},a_{jv}\right|^2} \tag{4}$$

The resource utilization indices should be assigned a large weight, because they have a relatively significantly effect on the detection of college students' online English learning behavior. By contrast, the communication and collaboration indices should be assigned a small weight. Let θ_1 and θ_2 be the weights of the resource utilization indices, and the communication and collaboration indices, respectively. Then, we have:

$$DIS_{CQ}\left(a_i,a_j\right)=\sqrt{\theta_1\left(a_{i1}-a_{j1}\right)^2+\theta_2\left(a_{i2}-a_{j2}\right)^2} \tag{5}$$

Our formative evaluation of college students' online English learning behavior covers four aspects: learning attitude, communication and collaboration, resource utilization, and self-reflection. Specifically, learning attitude covers four indices: total number of logins onto online platforms; total online time; total number of learning professional English courses; total time of learning professional English courses. Communication and collaboration covers six indices: times of answering questions; times of raising questions; times of joining topic discussions; times of evaluating others; number of self-evaluations; times of participating in voting. Resource utilization covers three indices: times of uploading resources; times of clicking on resources; times of downloading resources. Self-reflection covers two indices: times of course reflections; cumulative times of reflections.

Let t_l=1,2,...,$|b|$ be the proportion of data samples of type l college students' online English learning behavior in sample set E. The information entropy of E can be calculated by:

$$OCW\left(E\right)=-\sum_{l=1}^{|b|}t_l log_2 t_l \tag{6}$$

The smaller the value of $OCW(E)$, the greater the purity of samples in E.

This paper adopts the entropy value method to weigh each index for the formative evaluation of college students' online English learning behavior. The specific steps of index weighting are as follows:

Firstly, choose m data samples, and denote the value of the j-th index of the i-th sample by a_{ij}. To unify the measuring units of different indices, normalize the index data:

$$a_{ij}^{'}=\frac{a_{ij}-min\left(a_{1j},a_{2j},...,a_{mj}\right)}{max\left(a_{1j},a_{2j},...,a_{mj}\right)-min\left(a_{1j},a_{2j},...,a_{mj}\right)} \tag{7}$$

Compute the weight of the i-th data sample under the j-th index:

$$t_{ij} = \frac{a_{ij}^{'}}{\sum_{i=1}^{m} a_{ij}^{'}}, (i = 1, 2, ..., m) \tag{8}$$

Compute the entropy of the j-th index:

$$q_j = -l \sum_{i=1}^{m} t_{ij} ln(t_{ij}), l = 1/ln(m) \tag{9}$$

Compute the coefficient of variation of the j-th index:

$$h_j = 1 - q_i \tag{10}$$

Determine the weight of the j-th index:

$$\theta_j = \frac{h_j}{\sum_{j=1}^{n} h_j} \tag{11}$$

After the weights of the indices are determined by entropy weight method, compute the weighted distance between data samples based on their index weights, using the following distance matrix:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ \vdots & \vdots & \cdots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mm} \end{bmatrix} \tag{12}$$

Let w_{ij} be the weighted distance between data samples a_i and a_j. Sort the elements in each column of the matrix in ascending order, forming the element w_{li}' in the j-th column and l-th row in the new distance matrix W', i.e., the distance from a_i to the l-th farthest data sample:

$$W' = \begin{bmatrix} w'_{11} & w'_{12} & \cdots & w'_{1m} \\ \vdots & \vdots & \cdots & \vdots \\ w'_{m1} & w'_{m2} & \cdots & w'_{mm} \end{bmatrix} \tag{13}$$

Compute the mean of the elements in each row of W', and substitute the mean w'_l of the l-th row to the DBSCAN. When the number of clusters for formative evaluation and the number of abnormal samples tend to be stable, take the minimum w'_l as the neighborhood radius, i.e., $\rho = w'_l$.

3 Formative evaluation prediction

The behavioral features were extracted from the historical data on college students' online English learning behavior. Then, the authors analyzed the correlations between these features and the formative evaluation of online college English learning. Next, the graph attention network was adopted to predict whether the formative evaluation scores of the students are too low. In this way, the school precaution function of online English learning was realized through the graph structure data prediction of students' online learning behavior. This helps the online English learning platforms and teachers to ensure the smooth completion of English learning courses through effective interventions. Figure 1 shows the formative evaluation prediction network based on graph attention network. Obviously, the proposed network contains two graph attention networks, responsible for updating node features.

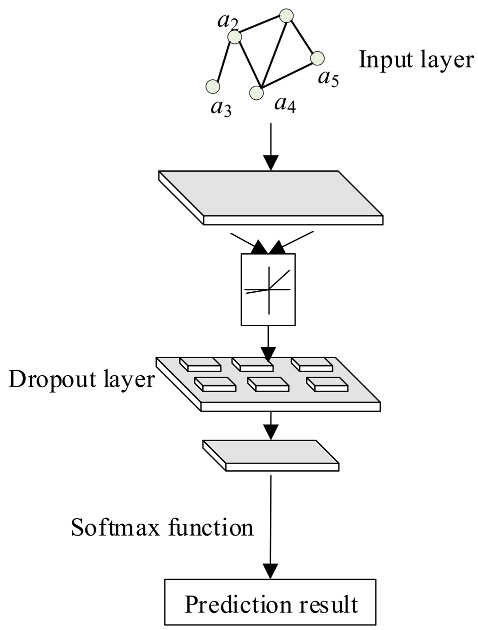

Fig. 1. Formative evaluation prediction network based on graph attention network

Let $f^{(k)}=\{f^{(k)}_1,f^{(k)}_2,\dots,f^{(k)}_M\}$ be the input of the nodes on the l-th layer in the proposed graph attention network; $f^k_i \in R^G$, G, and M be the feature set, feature dimension, and node number of the nodes on the l-th layer in the proposed graph attention network, respectively; $\gamma^{(k)} \in R^{G*G'}$ be the weight coefficient of the k-th layer; G' be the feature dimension of the nodes on the k+1-th layer. Then, the linear transformation formula can be established as:

$$C_i^{(k)} = \gamma^{(k)} f_i^{(k)} \tag{14}$$

After introducing the attention mechanism $\lambda \in R^{G^*G'}$ to the network, the attention correlation coefficient u_{ij} can be calculated by:

$$u_{ij} = \lambda\left(C_i^{(k)}, C_j^{(k)}\right) = \lambda\left(\gamma^{(k)} f_i^{(k)}, \gamma^{(k)} f_j^{(k)}\right) \tag{15}$$

The attention correlation coefficient u_{ij} reflects the degree of influence of node j on node i. The greater the coefficient, the more important node j is to node i. To measure the correlation coefficient between different nodes more accurately, the value range of u_{ij} was changed to [0, 1] based on the softmax function. After adding the nonlinear layer, the attention mechanism λ_{ij} can be expressed as:

$$\lambda_{ij} = softmax_j\left(u_{ij}\right) = \frac{exp\left(L\text{-}\mathrm{Re}LU\left(u_{ij}^{(k)}\right)\right)}{\sum_{l \in M_i} exp\left(L\text{-}\mathrm{Re}LU\left(u_{il}^{(k)}\right)\right)} \tag{16}$$

Let M_i be the set of neighbor nodes of node i. This set contains the node i, i.e., the output of each node is related to its adjacent nodes and itself. The output of node i on the l-th layer can be calculated by:

$$f_i^{(k+1)} = \Phi\left(\sum_{j \in M_i} \delta_{ij} \gamma^{(k)} f_j^{(k)}\right) \tag{17}$$

$\Phi(*)$ often adopts the *Sigmoid* function. To stabilize the proposed network, the learning process was enhanced by the multi-head attention mechanism (Figure 2). Let L be the number of heads in the mechanism. Then, the output of the mechanism can be calculated by two different methods: splicing, and averaging. Let < be the splicing operation; δ^l_{ij} and $\gamma^{(k)}{}_l$ be the normalized attention coefficient of the l-th head, and the corresponding weight coefficient matrix, respectively. Then, the splicing operation can be expressed as:

$$f_i^{(k+1)} = \mathop{\Big\langle}_{l=1}^{L} \Phi\left(\sum_{j \in M^i} \delta_{ij}^k \gamma_l^{(k)} f_j^{(k)}\right) \tag{18}$$

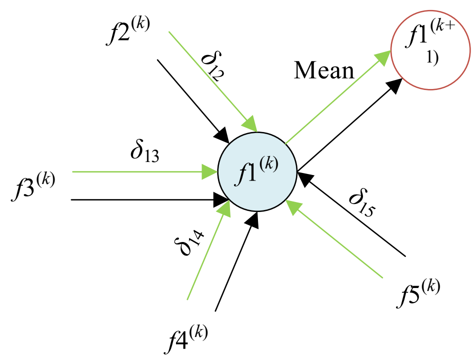

Fig. 2. An example of multi-head attention mechanism

The averaging operation can be expressed as:

$$f_i^{(k+1)} = \Phi\left(\frac{1}{L}\sum\nolimits_{l=1}^{L}\sum\nolimits_{j\in M^i}\delta_{ij}^l\gamma_l^{(k)}f_j^{(k)}\right) \tag{19}$$

In the graph attention network, the output of the nodes on the l-th layer can be calculated by:

$$f^{(k)} = \left\{f_1^{(k)}, f_2^{(k)}, \ldots, f_M^{(k)}\right\} \tag{20}$$

where, $f^k{}_i \in R^G$. The output of the nodes on the k-th layer equals the input of the nodes on the k+1-th layer:

$$f^{(k+1)} = \left\{f_1^{(k+1)}, f_2^{(k+1)}, \ldots, f_M^{(k+1)}\right\} \tag{21}$$

where, $`f^{(k+)}{}_i \in R^{G`}$, i.e., each node has G' features after feature update. To realize the mapping from the input layer to the output layer in the graph attention network, it is first needed to linearly transform the features of the input layer nodes, producing the weight coefficient matrix $Q^k \in R^{G*G`}$. Then, the feature dimension of the nodes changes from G to G'.

To obtain the feature map of the nodes on the k+1-th layer, it is necessary to update the node features on that layer by the following rule:

$$f_i^{(k+1)} = \underset{l=1}{\overset{L}{}}\Big\langle \Phi\left(\sum\nolimits_{j\in M^i}\delta_{ij}^l\gamma_l^{(k)}f_j^{(k)}\right) \tag{22}$$

For the formative evaluation prediction of college students' online English learning, the higher similarity between students in early-stage learning behavior, the greater the possibility for them to achieve the same effect of online English learning in the late stage. Therefore, this paper introduces the clustering Euclidean distance weight was introduced to measure the similarity between two nodes, based on the proposed graph neural network. Figure 3 explains the weight update process of the attention mechanism with clustering distance weight.

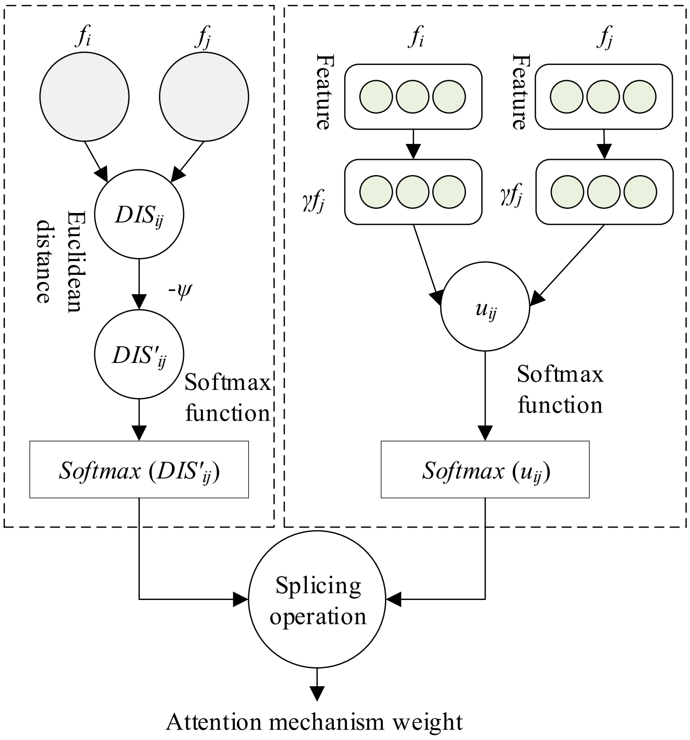

Fig. 3. An example of attention mechanism with clustering distance weight

4 Experiments and results analysis

Table 1 presents the descriptive statistics on communication and collaboration indices for the data samples on college students' online English learning behavior. The data samples were divided into an in-class group, and an after-class group. Out of the 289 data samples on communication and collaboration indices, 14 data samples were identified as after-class communication and collaboration behavior, and the mean score, standard deviation, and confidence interval of the corresponding indices were 26.137, 9.5862, and [16.374,25.483], respectively. Meanwhile, 275 data samples were identified as in-class communication and collaboration behavior, and the mean score, standard deviation, and confidence interval of the corresponding indices were 25.061, 6.3527, and [27.192, 28.618], respectively. Out of all data samples, 95.2% were relatively clustered, and identified as in-class communication and collaboration behavior. Compared with the after-class behavior, the in-class behavior had relatively small confidence range, and standard deviation. These results are consistent with the fact.

Table 1. Descriptive statistics on communication and collaboration indices

	In-class	After-class	Total	Model	
				Random effects	***Fixed effects***
Number of tested samples	275	14	289	/	/
Mean	25.061	23.137	27.852	/	/
Standard deviation	6.3527	9.5862	6.1741	6.2953	/
Standard error	3.085	3.2658	3.162	3.486	4.703
Lower bound of confidence interval	27.192	16.374	29.185	26.591	-29.482
Upper bound of confidence interval	28.618	25.483	24.681	26.398	85.418

Table 2 displays the descriptive statistics on resource utilization indices for the data samples on college students' online English learning behavior. The data samples were still divided into an in-class group, and an after-class group. Out of the 287 data samples on resource utilization indices, 19 data samples were identified as after-class resource utilization behavior, and the mean score, standard deviation, and confidence interval of the corresponding indices were 26. 253.71, 152.63, and [168.47,368.02], respectively. Meanwhile, 268 data samples were identified as in-class resource utilization behavior, and the mean score, standard deviation, and confidence interval of the corresponding indices were 96.26, 16.282, and [92.85, 95.17], respectively. Out of all data samples, 93.3% were relatively clustered, and identified as in-class resource utilization behavior. Compared with the after-class behavior, the in-class behavior had relatively small confidence range, and standard deviation. These results are consistent with the fact, too.

The minimum number of samples in the neighborhood is a key parameter of DBSCAN. Considering the data features of college students' online English learning behavior, this paper determines the minimum number of samples in the neighborhood through experiments. The neighborhood radius and minimum number of samples in the neighborhood were set to different values for the test set. Figures 4 and 5 record how the number of classes, and number of abnormal samples vary with the minimum number of samples in the neighborhood, respectively.

Table 2. Descriptive statistics on resource utilization indices

	In-class	After-class	Total	Model	
				Random effects	***Fixed effects***
Number of tested samples	268	19	287	/	/
Mean	96.26	253.71	98.52	/	/
Standard deviation	16.282	152.63	42.18	33.64	/
Standard error	1.027	46.135	2.695	1.628	125.483
Lower bound of confidence interval	92.85	168.47	96.46	91.71	-1628.92
Upper bound of confidence interval	95.17	368.02	115.35	141.96	1849.28

As shown in Figure 4, the neighborhood radius changed from 2, 4, 6, 8, 10, 12, to 14. When the minimum number of samples in the neighborhood was smaller than 5, the number of classes declined with the growth of that number; When the number was greater than 5, the number of classes tended to be stable.

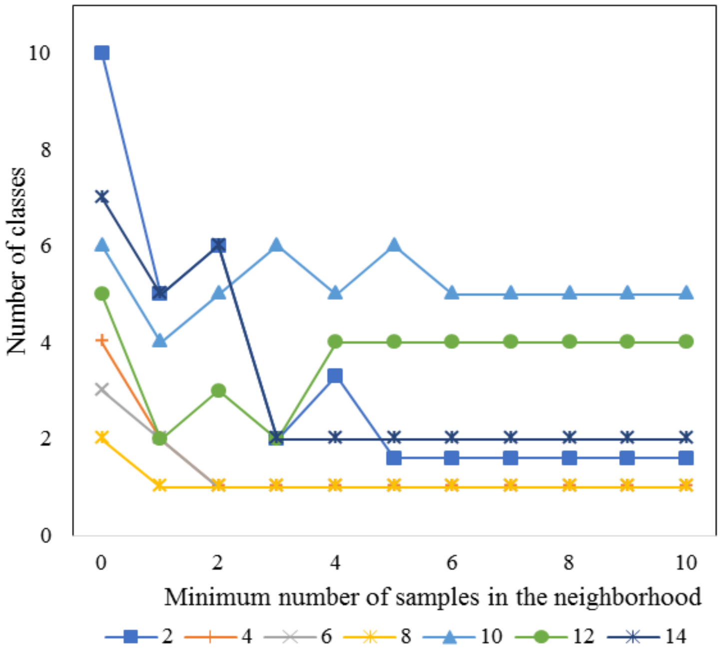

Fig. 4. Variation in the number of classes with the minimum number of samples in the neighborhood

As shown in Figure 5, when the minimum number of samples in the neighborhood was smaller than 5, the number of abnormal samples changed with the said number, regardless of the neighborhood radius. When the number of equal to or greater than 5, the number of abnormal samples tended to be stable. Overall, it is suitable to set the minimum number of samples in the neighborhood to 5.

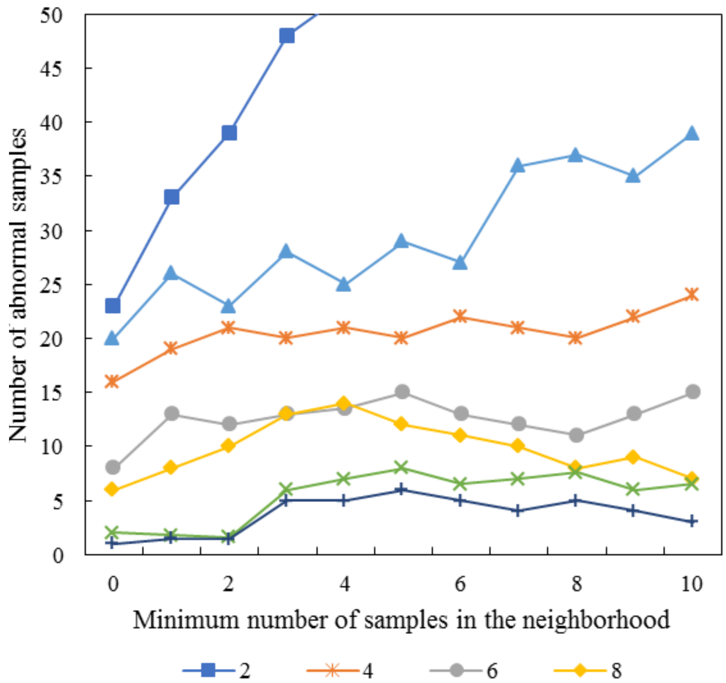

Fig. 5. Variation in the number of abnormal samples with the minimum number of samples in the neighborhood

The clustering result is reported in Figure 6, where the data samples allocated to the same class of learning behavior are marked in the same color, and the scattered abnormal samples are not marked. The clustering result is consistent with the features of college students' online English learning behavior.

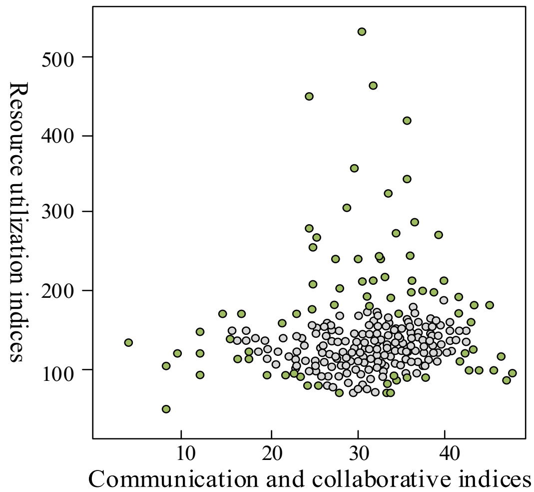

Fig. 6. An example of clustering result

Table 3 compares the formative evaluation prediction results of different models. Our network achieved a better prediction effect than the basic networks, namely, backpropagation neural network, convolutional neural network, and graph convolutional neural network. The precision, recall, F1-score, and accuracy of our network were 0.89, 0.85, 0.87, and 0.89, respectively. Figure 7 presents the prediction results on the formative evaluation. It can be seen that the four metrics of prediction performance of our network were all on the rise. Recall achieved the most prominent rise (7.5%). F1-score increased by about 6.5%.

Table 3. Formative evaluation prediction results of different models

Model	Backpropagation neural network	Convolutional neural network	Graph convolutional neural network	Our network
Precision	0.71	0.73	0.76	0.89
Recall	0.75	0.70	0.72	0.85
F1-score	0.72	0.76	0.74	0.87
Accuracy	0.82	0.86	0.88	0.89

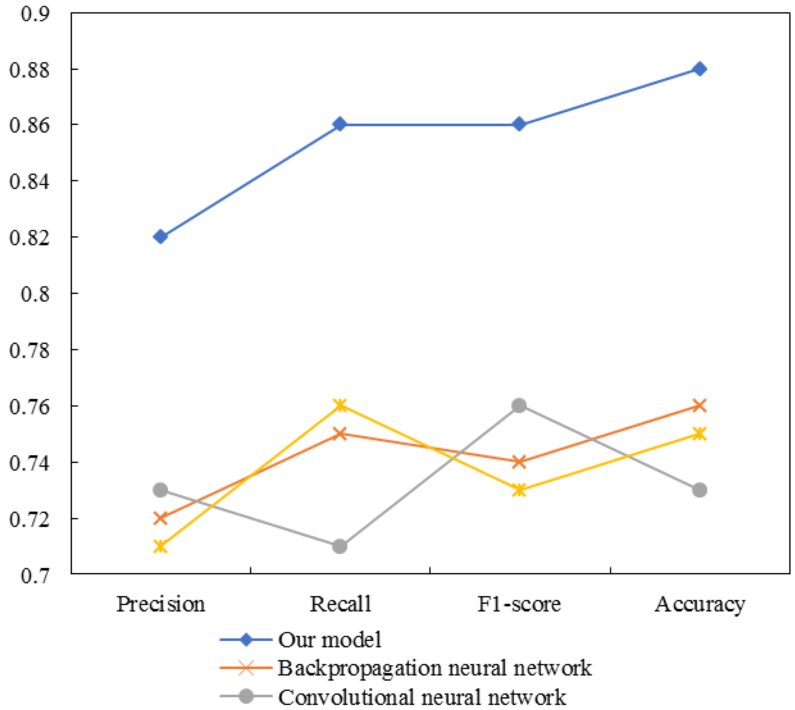

Fig. 7. Prediction results on the formative evaluation

5 Conclusions

This paper mainly deals with the formative evaluation of college students' online English learning based on learning behavior analysis. Firstly, the data samples of college students' online English learning behavior were examined by DBSCAN, before selecting the formative evaluation indices. Based on the graph structure data prediction of students' online learning behavior, the authors realized the school precaution function of online English learning. In addition, the clustering Euclidean distance weight was introduced to measure the similarity between two nodes, based on the proposed graph neural network. Through experiments, the authors obtained the descriptive statistics on the data samples of college students' online English learning behavior under two indices (communication and collaboration, and the resource utilization). The statistics show that the data samples of in-class behavior had smaller confidence interval and standard deviation than those of after-class behavior. This conclusion agrees with the reality. Besides, the authors recorded the variation in the number of classes and number of abnormal samples for college students' online English learning behavior, and determined a suitable minimum number of samples in the neighborhood. After that, the clustering result was plotted, and the formative evaluation prediction results of different models were compared, revealing that our network achieved a better prediction effect than the basic networks, namely, backpropagation neural network, convolutional neural network, and graph convolutional neural network.

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Article submitted 2022-03-11. Resubmitted 2022-03-12. Final acceptance 2022-04-13. Final version published as submitted by the authors.